autogluon_each_location

October 7, 2023

[96]:
```python
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")

    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = 3
    X_test["sample_weight"] = 3

    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
 ↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600
```

```python
    X_train_estimated["estimated_diff_hours"] = X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])

    # fill missng sample_weight with 3
    #X_train["sample_weight"] = X_train["sample_weight"].fillna(0)


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True, right_index=True)

    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")
```

```python
    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[97]:
```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
# weekday or is_weekend
X_train["is_weekend"] = X_train["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_train.drop(columns=["weekday"], inplace=True)
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday

# weekday or is_weekend
X_test["is_weekend"] = X_test["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_test.drop(columns=["weekday"], inplace=True)
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year



to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

[98]:
```
import autogluon.eda.auto as auto
auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",␣
↪sample=None)
```

train_data dataset summary

```
                          count  unique top   freq          mean  \
absolute_humidity_2m:gm3   92951    165                  6.017608
air_density_2m:kgm3        92951    293                  1.255435
ceiling_height_agl:m       72276  40993               2802.587891
clear_sky_energy_1h:J      92951  48602              515154.03125
clear_sky_rad:W            92951   7815                143.101395
cloud_base_agl:m           84404  34862               1692.934692
```

dew_or_rime:idx	92951	3			0.007025
dew_point_2m:K	92951	436			275.237823
diffuse_rad:W	92951	2870			39.495811
diffuse_rad_1h:J	92951	48553			142180.03125
direct_rad:W	92951	5296			50.205017
direct_rad_1h:J	92951	41885			180740.1875
effective_cloud_cover:p	92951	1001			67.013527
elevation:m	92951	3			11.401738
estimated_diff_hours	92951	26			3.143516
fresh_snow_12h:cm	92951	125			0.116175
fresh_snow_1h:cm	92951	39			0.00963
fresh_snow_24h:cm	92951	161			0.229894
fresh_snow_3h:cm	92951	70			0.029001
fresh_snow_6h:cm	92951	96			0.058069
hour	92951	24			11.501339
is_day:idx	92951	2			0.483341
is_in_shadow:idx	92951	2			0.565384
is_weekend	92951	2			0.286775
location	92951	3	A	34061	
month	92951	12			6.294521
msl_pressure:hPa	92951	874			1009.502563
precip_5min:mm	92951	64			0.005674
precip_type_5min:idx	92951	7			0.083259
pressure_100m:hPa	92951	888			995.81897
pressure_50m:hPa	92951	897			1001.949646
prob_rime:p	92951	700			0.756834
rain_water:kgm2	92951	11			0.009677
relative_humidity_1000hPa:p	92951	788			73.669556
sample_weight	92951	2			1.23507
sfc_pressure:hPa	92951	902			1008.107849
snow_depth:cm	92951	165			0.193203
snow_melt_10min:mm	92951	19			0.000275
snow_water:kgm2	92951	42			0.090324
sun_azimuth:d	92951	69692			182.386337
sun_elevation:d	92951	49376			-1.207574
super_cooled_liquid_water:kgm2	92951	15			0.056944
t_1000hPa:K	92951	447			279.431091
total_cloud_cover:p	92951	1001			73.604256
visibility:m	92951	85686			33027.933594
weekday	92951	7			3.002184
wind_speed_10m:ms	92951	119			3.037911
wind_speed_u_10m:ms	92951	188			0.662565
wind_speed_v_10m:ms	92951	167			0.6824
wind_speed_w_1000hPa:ms	92951	3			-0.000016
y	92951	12423			287.232321
year	92951	5			2020.693193

std min 25% \

absolute_humidity_2m:gm3	2.714546	0.5	4.0
air_density_2m:kgm3	0.036608	1.139	1.23
ceiling_height_agl:m	2521.408447	27.799999	1037.099976
clear_sky_energy_1h:J	820525.5	0.0	0.0
clear_sky_rad:W	228.507324	0.0	0.0
cloud_base_agl:m	1790.963745	27.4	572.200012
dew_or_rime:idx	0.246032	-1.0	0.0
dew_point_2m:K	6.83461	247.300003	270.700012
diffuse_rad:W	60.647518	0.0	0.0
diffuse_rad_1h:J	215907.21875	0.0	0.0
direct_rad:W	112.946068	0.0	0.0
direct_rad_1h:J	401735.03125	0.0	0.0
effective_cloud_cover:p	35.044811	0.0	41.299999
elevation:m	7.877236	6.0	6.0
estimated_diff_hours	8.935328	0.0	0.0
fresh_snow_12h:cm	0.780374	0.0	0.0
fresh_snow_1h:cm	0.112621	0.0	0.0
fresh_snow_24h:cm	1.218249	0.0	0.0
fresh_snow_3h:cm	0.28067	0.0	0.0
fresh_snow_6h:cm	0.481389	0.0	0.0
hour	6.920153	0.0	6.0
is_day:idx	0.499725	0.0	0.0
is_in_shadow:idx	0.495709	0.0	0.0
is_weekend	0.452258	0.0	0.0
location			
month	3.585604	1.0	3.0
msl_pressure:hPa	13.089046	944.299988	1001.400024
precip_5min:mm	0.033511	0.0	0.0
precip_type_5min:idx	0.384904	0.0	0.0
pressure_100m:hPa	13.008334	929.799988	987.799988
pressure_50m:hPa	13.067102	935.599976	993.900024
prob_rime:p	5.434649	0.0	0.0
rain_water:kgm2	0.042968	0.0	0.0
relative_humidity_1000hPa:p	14.328553	19.5	64.199997
sample_weight	0.644117	1.0	1.0
sfc_pressure:hPa	13.128181	941.400024	1000.0
snow_depth:cm	1.254293	0.0	0.0
snow_melt_10min:mm	0.004312	-0.0	-0.0
snow_water:kgm2	0.250991	0.0	0.0
sun_azimuth:d	102.913605	0.008	92.794003
sun_elevation:d	24.010485	-49.979	-18.511
super_cooled_liquid_water:kgm2	0.111482	0.0	0.0
t_1000hPa:K	6.520342	257.899994	274.899994
total_cloud_cover:p	34.993042	0.0	51.700001
visibility:m	18319.150391	130.600006	15798.950195
weekday	2.001722	0.0	1.0
wind_speed_10m:ms	1.778505	0.0	1.7
wind_speed_u_10m:ms	2.808995	-7.3	-1.4

wind_speed_v_10m:ms	1.896996	-9.3	-0.6
wind_speed_w_1000hPa:ms	0.006502	-0.1	0.0
y	766.670114	-0.0	0.0
year	1.18587	2019.0	2020.0

	50%	75%	max \
absolute_humidity_2m:gm3	5.4	7.8	17.5
air_density_2m:kgm3	1.255	1.279	1.441
ceiling_height_agl:m	1803.25	3814.824951	12431.299805
clear_sky_energy_1h:J	4544.899902	778247.25	3006697.25
clear_sky_rad:W	0.0	220.949997	835.299988
cloud_base_agl:m	1128.550049	2016.699951	11688.900391
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	275.0	280.5	293.799988
diffuse_rad:W	0.0	66.0	340.100006
diffuse_rad_1h:J	9951.700195	236502.75	1182265.375
direct_rad:W	0.0	29.0	684.299988
direct_rad_1h:J	0.0	113366.25	2445897.0
effective_cloud_cover:p	80.800003	99.300003	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	0.0	0.0	39.0
fresh_snow_12h:cm	0.0	0.0	37.400002
fresh_snow_1h:cm	0.0	0.0	7.1
fresh_snow_24h:cm	0.0	0.0	37.400002
fresh_snow_3h:cm	0.0	0.0	20.6
fresh_snow_6h:cm	0.0	0.0	34.0
hour	12.0	17.0	23.0
is_day:idx	0.0	1.0	1.0
is_in_shadow:idx	1.0	1.0	1.0
is_weekend	0.0	1.0	1.0
location			
month	6.0	10.0	12.0
msl_pressure:hPa	1010.299988	1018.599976	1044.099976
precip_5min:mm	0.0	0.0	1.38
precip_type_5min:idx	0.0	0.0	6.0
pressure_100m:hPa	996.799988	1004.900024	1030.900024
pressure_50m:hPa	1002.900024	1011.099976	1037.300049
prob_rime:p	0.0	0.0	97.199997
rain_water:kgm2	0.0	0.0	1.4
relative_humidity_1000hPa:p	76.0	85.099998	100.0
sample_weight	1.0	1.0	3.0
sfc_pressure:hPa	1009.0	1017.200012	1043.800049
snow_depth:cm	0.0	0.0	18.299999
snow_melt_10min:mm	0.0	-0.0	0.18
snow_water:kgm2	0.0	0.1	6.9
sun_azimuth:d	179.526001	271.503494	359.997009
sun_elevation:d	-0.99	15.538	49.917999
super_cooled_liquid_water:kgm2	0.0	0.1	1.4

t_1000hPa:K	278.700012	283.899994	303.299988
total_cloud_cover:p	94.800003	100.0	100.0
visibility:m	37350.300781	48679.550781	76737.796875
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.1	15.2
wind_speed_u_10m:ms	0.3	2.5	12.2
wind_speed_v_10m:ms	0.7	1.9	9.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
y	0.0	173.3625	5733.42
year	2021.0	2022.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	float32			float
air_density_2m:kgm3	float32			float
ceiling_height_agl:m	float32	20675	0.222429	float
clear_sky_energy_1h:J	float32			float
clear_sky_rad:W	float32			float
cloud_base_agl:m	float32	8547	0.091952	float
dew_or_rime:idx	float32			float
dew_point_2m:K	float32			float
diffuse_rad:W	float32			float
diffuse_rad_1h:J	float32			float
direct_rad:W	float32			float
direct_rad_1h:J	float32			float
effective_cloud_cover:p	float32			float
elevation:m	float32			float
estimated_diff_hours	int64			int
fresh_snow_12h:cm	float32			float
fresh_snow_1h:cm	float32			float
fresh_snow_24h:cm	float32			float
fresh_snow_3h:cm	float32			float
fresh_snow_6h:cm	float32			float
hour	int64			int
is_day:idx	float32			float
is_in_shadow:idx	float32			float
is_weekend	int64			int
location	object			object
month	int64			int
msl_pressure:hPa	float32			float
precip_5min:mm	float32			float
precip_type_5min:idx	float32			float
pressure_100m:hPa	float32			float
pressure_50m:hPa	float32			float
prob_rime:p	float32			float
rain_water:kgm2	float32			float
relative_humidity_1000hPa:p	float32			float
sample_weight	int64			int
sfc_pressure:hPa	float32			float

snow_depth:cm	float32	float
snow_melt_10min:mm	float32	float
snow_water:kgm2	float32	float
sun_azimuth:d	float32	float
sun_elevation:d	float32	float
super_cooled_liquid_water:kgm2	float32	float
t_1000hPa:K	float32	float
total_cloud_cover:p	float32	float
visibility:m	float32	float
weekday	int64	int
wind_speed_10m:ms	float32	float
wind_speed_u_10m:ms	float32	float
wind_speed_v_10m:ms	float32	float
wind_speed_w_1000hPa:ms	float32	float
y	float64	float
year	int64	int

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
estimated_diff_hours	numeric	
fresh_snow_12h:cm	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_in_shadow:idx	category	
is_weekend	category	
location	category	
month	category	
msl_pressure:hPa	numeric	
precip_5min:mm	numeric	
precip_type_5min:idx	category	
pressure_100m:hPa	numeric	

pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	category
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric
year	category

test_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	2160	106			8.206482	
air_density_2m:kgm3	2160	153			1.232807	
ceiling_height_agl:m	1473	1391			2938.389648	
clear_sky_energy_1h:J	2160	1807			1227746.75	
clear_sky_rad:W	2160	1044			341.056641	
cloud_base_agl:m	1879	1771			1797.160156	
dew_or_rime:idx	2160	3			0.040741	
dew_point_2m:K	2160	202			280.783203	
diffuse_rad:W	2160	985			84.915688	
diffuse_rad_1h:J	2160	1806			305696.5	
direct_rad:W	2160	916			114.279816	
direct_rad_1h:J	2160	1634			411408.875	
effective_cloud_cover:p	2160	590			64.113792	
elevation:m	2160	3			12.333333	
estimated_diff_hours	2160	24			27.5	
fresh_snow_12h:cm	2160	2			0.000185	
fresh_snow_1h:cm	2160	2			0.000185	
fresh_snow_24h:cm	2160	2			0.000185	
fresh_snow_3h:cm	2160	2			0.000185	
fresh_snow_6h:cm	2160	2			0.000185	
hour	2160	24			11.5	
is_day:idx	2160	2			0.795833	
is_in_shadow:idx	2160	2			0.24537	

is_weekend	2160	2			0.366667
location	2160	3	A	720	
month	2160	3			5.666667
msl_pressure:hPa	2160	321			1016.805786
precip_5min:mm	2160	27			0.00775
precip_type_5min:idx	2160	3			0.065741
pressure_100m:hPa	2160	359			1002.970825
pressure_50m:hPa	2160	356			1009.007202
prob_rime:p	2160	3			0.01588
rain_water:kgm2	2160	8			0.013056
relative_humidity_1000hPa:p	2160	538			70.920792
sample_weight	2160	1			3.0
sfc_pressure:hPa	2160	363			1015.070374
snow_depth:cm	2160	1			0.0
snow_melt_10min:mm	2160	1			0.0
snow_water:kgm2	2160	16			0.060972
sun_azimuth:d	2160	1830			183.166199
sun_elevation:d	2160	1623			20.292332
super_cooled_liquid_water:kgm2	2160	7			0.065463
t_1000hPa:K	2160	254			284.737732
total_cloud_cover:p	2160	553			69.298981
visibility:m	2160	2155			33304.636719
weekday	2160	7			3.233333
wind_speed_10m:ms	2160	83			2.946759
wind_speed_u_10m:ms	2160	123			1.650694
wind_speed_v_10m:ms	2160	80			-0.187176
wind_speed_w_1000hPa:ms	2160	2			0.000324
year	2160	1			2023.0

	std	min	25%	\
absolute_humidity_2m:gm3	2.201396	3.2	6.6	
air_density_2m:kgm3	0.032116	1.142	1.209	
ceiling_height_agl:m	2913.641113	30.6	891.799988	
clear_sky_energy_1h:J	1104468.625	0.0	64338.124023	
clear_sky_rad:W	307.729095	0.0	13.65	
cloud_base_agl:m	2046.394409	29.799999	486.899994	
dew_or_rime:idx	0.202365	-1.0	0.0	
dew_point_2m:K	4.378817	268.0	277.899994	
diffuse_rad:W	78.422508	0.0	6.925	
diffuse_rad_1h:J	278146.25	0.0	36756.901367	
direct_rad:W	171.838226	0.0	0.0	
direct_rad_1h:J	611480.125	0.0	86.575001	
effective_cloud_cover:p	37.947498	0.0	30.700001	
elevation:m	8.261587	6.0	6.0	
estimated_diff_hours	6.923789	16.0	21.75	
fresh_snow_12h:cm	0.008607	0.0	0.0	
fresh_snow_1h:cm	0.008607	0.0	0.0	
fresh_snow_24h:cm	0.008607	0.0	0.0	

fresh_snow_3h:cm	0.008607	0.0	0.0
fresh_snow_6h:cm	0.008607	0.0	0.0
hour	6.923789	0.0	5.75
is_day:idx	0.403185	0.0	1.0
is_in_shadow:idx	0.430406	0.0	0.0
is_weekend	0.482006	0.0	0.0
location			
month	0.596423	5.0	5.0
msl_pressure:hPa	9.728754	986.099976	1011.5
precip_5min:mm	0.033776	0.0	0.0
precip_type_5min:idx	0.249747	0.0	0.0
pressure_100m:hPa	9.644145	971.799988	997.799988
pressure_50m:hPa	9.74076	977.700012	1003.799988
prob_rime:p	0.551282	0.0	0.0
rain_water:kgm2	0.055256	0.0	0.0
relative_humidity_1000hPa:p	15.725973	23.9	60.275
sample_weight	0.0	3.0	3.0
sfc_pressure:hPa	9.840412	983.5	1009.799988
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	-0.0	-0.0
snow_water:kgm2	0.219562	0.0	0.0
sun_azimuth:d	109.193207	8.27	85.359253
sun_elevation:d	18.681047	-11.617	1.96475
super_cooled_liquid_water:kgm2	0.115824	0.0	0.0
t_1000hPa:K	5.839595	273.700012	279.799988
total_cloud_cover:p	38.41222	0.0	32.799999
visibility:m	15624.633789	874.400024	19635.100098
weekday	2.186573	0.0	1.0
wind_speed_10m:ms	1.733865	0.0	1.5
wind_speed_u_10m:ms	2.578466	-4.3	-0.2
wind_speed_v_10m:ms	1.50826	-4.4	-1.3
wind_speed_w_1000hPa:ms	0.005685	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max \
absolute_humidity_2m:gm3	8.0	10.0	14.2
air_density_2m:kgm3	1.238	1.26	1.301
ceiling_height_agl:m	1553.900024	4021.300049	11468.0
clear_sky_energy_1h:J	1056303.125	2372037.5	3005707.0
clear_sky_rad:W	273.849991	646.874985	835.099976
cloud_base_agl:m	997.799988	2298.300049	11467.799805
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	281.0	284.299988	290.200012
diffuse_rad:W	73.700001	135.600006	312.600006
diffuse_rad_1h:J	272526.046875	488256.03125	1086246.25
direct_rad:W	16.200001	180.399994	668.0
direct_rad_1h:J	60416.199219	686746.859375	2403444.25
effective_cloud_cover:p	77.75	100.0	100.0

elevation:m	7.0	24.0	24.0
estimated_diff_hours	27.5	33.25	39.0
fresh_snow_12h:cm	0.0	0.0	0.4
fresh_snow_1h:cm	0.0	0.0	0.4
fresh_snow_24h:cm	0.0	0.0	0.4
fresh_snow_3h:cm	0.0	0.0	0.4
fresh_snow_6h:cm	0.0	0.0	0.4
hour	11.5	17.25	23.0
is_day:idx	1.0	1.0	1.0
is_in_shadow:idx	0.0	0.0	1.0
is_weekend	0.0	1.0	1.0
location			
month	6.0	6.0	7.0
msl_pressure:hPa	1020.599976	1023.799988	1029.599976
precip_5min:mm	0.0	0.0	0.34
precip_type_5min:idx	0.0	0.0	2.0
pressure_100m:hPa	1006.25	1010.099976	1016.400024
pressure_50m:hPa	1012.299988	1016.200012	1022.5
prob_rime:p	0.0	0.0	23.0
rain_water:kgm2	0.0	0.0	0.7
relative_humidity_1000hPa:p	73.900002	83.699997	98.900002
sample_weight	3.0	3.0	3.0
sfc_pressure:hPa	1018.299988	1022.299988	1028.699951
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	0.0	0.0
snow_water:kgm2	0.0	0.0	3.4
sun_azimuth:d	184.236	279.576248	356.984009
sun_elevation:d	18.54	38.102499	49.902
super_cooled_liquid_water:kgm2	0.0	0.1	0.6
t_1000hPa:K	284.799988	288.299988	302.200012
total_cloud_cover:p	95.300003	100.0	100.0
visibility:m	37623.050781	45378.099609	63863.800781
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.0	8.8
wind_speed_u_10m:ms	1.6	3.525	8.8
wind_speed_v_10m:ms	-0.3	0.8	4.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
year	2023.0	2023.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type \
absolute_humidity_2m:gm3	float32			float
air_density_2m:kgm3	float32			float
ceiling_height_agl:m	float32	687	0.318056	float
clear_sky_energy_1h:J	float32			float
clear_sky_rad:W	float32			float
cloud_base_agl:m	float32	281	0.130093	float
dew_or_rime:idx	float32			float
dew_point_2m:K	float32			float

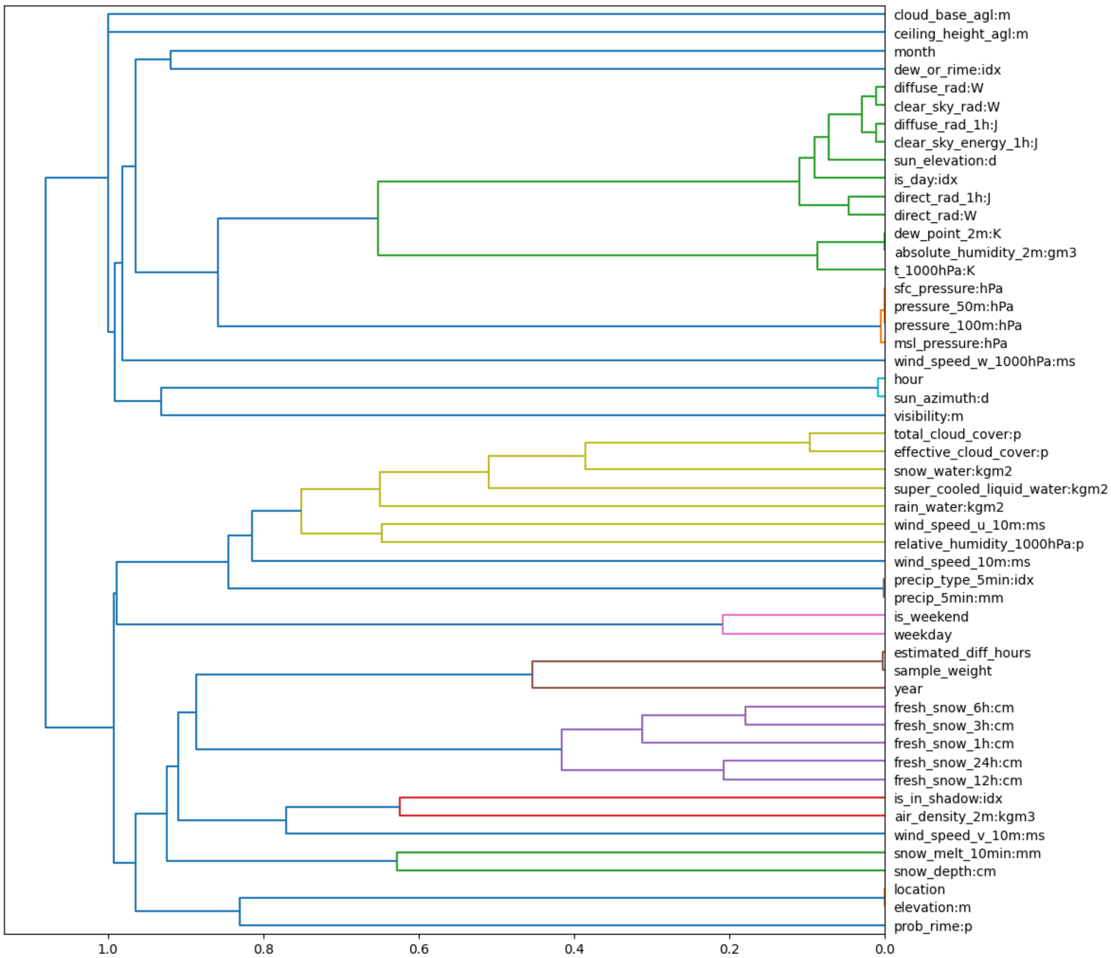
```
diffuse_rad:W                  float32                                   float
diffuse_rad_1h:J               float32                                   float
direct_rad:W                   float32                                   float
direct_rad_1h:J                float32                                   float
effective_cloud_cover:p        float32                                   float
elevation:m                    float32                                   float
estimated_diff_hours             int64                                     int
fresh_snow_12h:cm              float32                                   float
fresh_snow_1h:cm               float32                                   float
fresh_snow_24h:cm              float32                                   float
fresh_snow_3h:cm               float32                                   float
fresh_snow_6h:cm               float32                                   float
hour                             int64                                     int
is_day:idx                     float32                                   float
is_in_shadow:idx               float32                                   float
is_weekend                       int64                                     int
location                        object                                  object
month                            int64                                     int
msl_pressure:hPa               float32                                   float
precip_5min:mm                 float32                                   float
precip_type_5min:idx           float32                                   float
pressure_100m:hPa              float32                                   float
pressure_50m:hPa               float32                                   float
prob_rime:p                    float32                                   float
rain_water:kgm2                float32                                   float
relative_humidity_1000hPa:p    float32                                   float
sample_weight                    int64                                     int
sfc_pressure:hPa               float32                                   float
snow_depth:cm                  float32                                   float
snow_melt_10min:mm             float32                                   float
snow_water:kgm2                float32                                   float
sun_azimuth:d                  float32                                   float
sun_elevation:d                float32                                   float
super_cooled_liquid_water:kgm2 float32                                   float
t_1000hPa:K                    float32                                   float
total_cloud_cover:p            float32                                   float
visibility:m                   float32                                   float
weekday                          int64                                     int
wind_speed_10m:ms              float32                                   float
wind_speed_u_10m:ms            float32                                   float
wind_speed_v_10m:ms            float32                                   float
wind_speed_w_1000hPa:ms        float32                                   float
year                             int64                                     int

                              variable_type special_types
absolute_humidity_2m:gm3            numeric
air_density_2m:kgm3                 numeric
ceiling_height_agl:m                numeric
```

clear_sky_energy_1h:J	numeric
clear_sky_rad:W	numeric
cloud_base_agl:m	numeric
dew_or_rime:idx	category
dew_point_2m:K	numeric
diffuse_rad:W	numeric
diffuse_rad_1h:J	numeric
direct_rad:W	numeric
direct_rad_1h:J	numeric
effective_cloud_cover:p	numeric
elevation:m	category
estimated_diff_hours	numeric
fresh_snow_12h:cm	category
fresh_snow_1h:cm	category
fresh_snow_24h:cm	category
fresh_snow_3h:cm	category
fresh_snow_6h:cm	category
hour	numeric
is_day:idx	category
is_in_shadow:idx	category
is_weekend	category
location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	category
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	category
snow_melt_10min:mm	category
snow_water:kgm2	category
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
year	category

Types warnings summary

	train_data	test_data	warnings
y	float	--	warning

1.0.1 Feature Distance

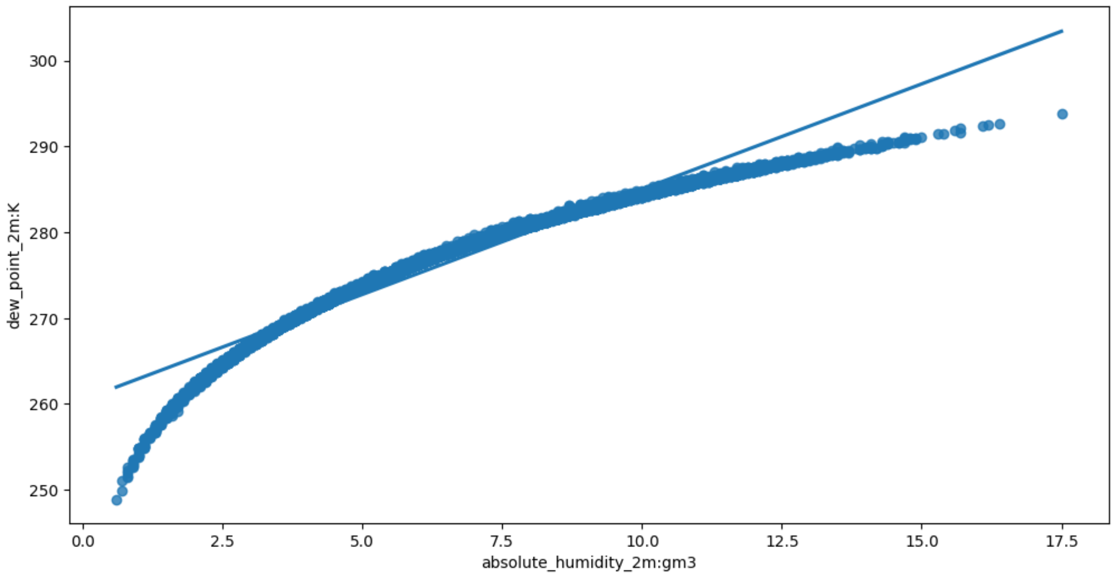


The following feature groups are considered as near-duplicates:

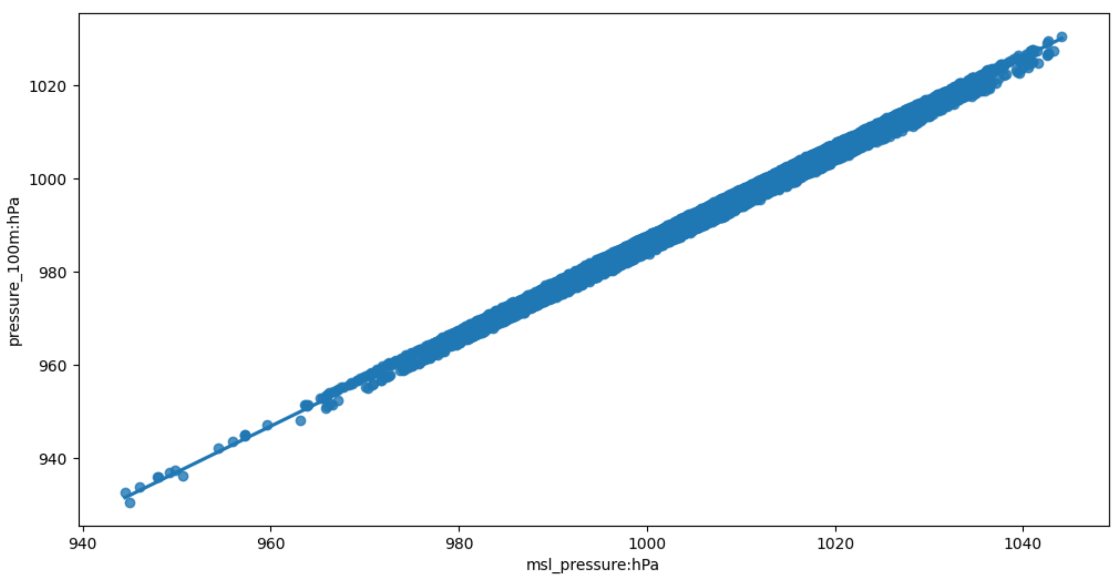
Distance threshold: <= `0.01`. Consider keeping only some of the columns within each group:

- `elevation:m`, `location` - distance `0.00`
- `absolute_humidity_2m:gm3`, `dew_point_2m:K` - distance `0.00`
- `precip_5min:mm`, `precip_type_5min:idx` - distance `0.00`
- `estimated_diff_hours`, `sample_weight` - distance `0.00`
- `msl_pressure:hPa`, `pressure_100m:hPa`, `pressure_50m:hPa`, `sfc_pressure:hPa` - distance `0.00`
- `hour`, `sun_azimuth:d` - distance `0.01`

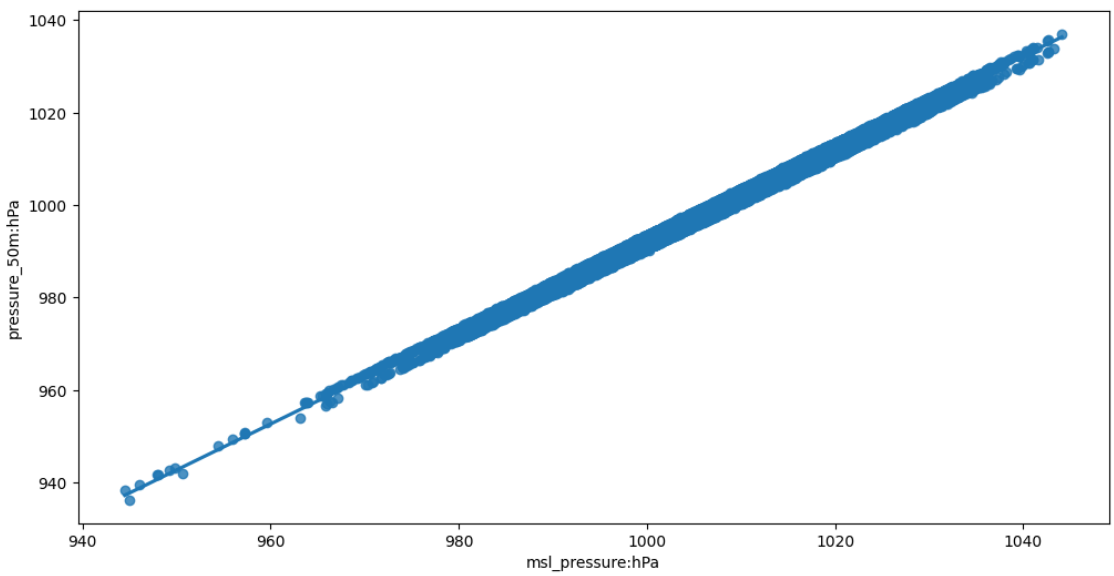
Feature interaction between `absolute_humidity_2m:gm3`/`dew_point_2m:K`



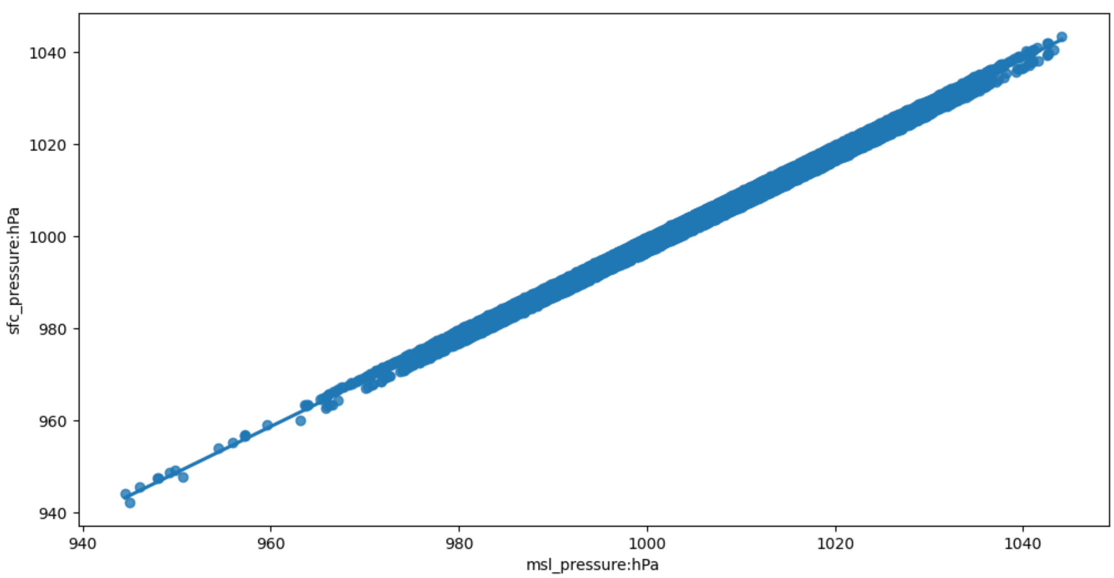
Feature interaction between `msl_pressure:hPa/pressure_100m:hPa`



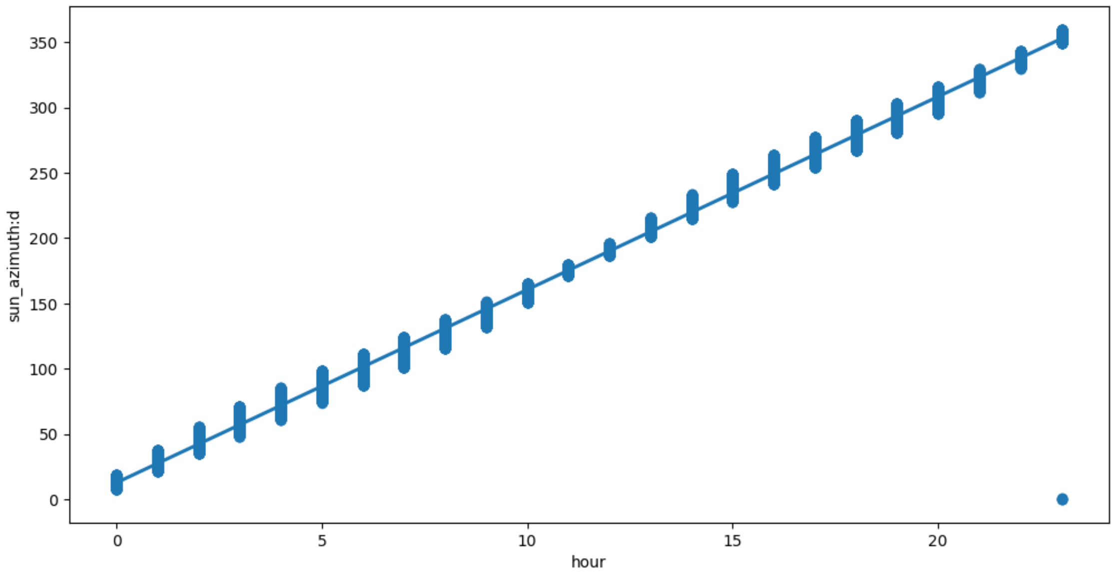
Feature interaction between `msl_pressure:hPa/pressure_50m:hPa`



Feature interaction between `msl_pressure:hPa`/`sfc_pressure:hPa`



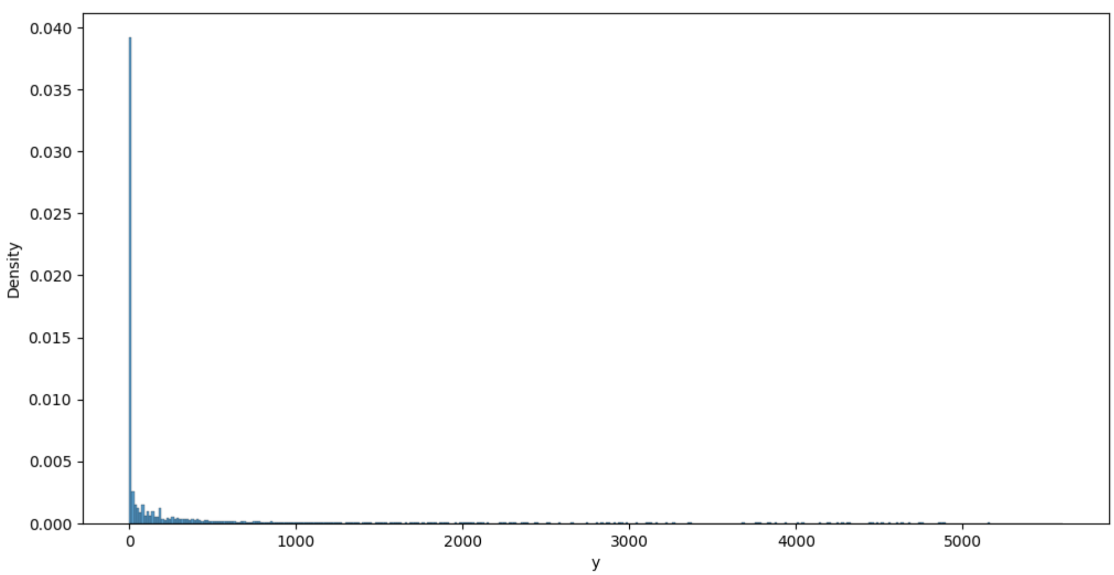
Feature interaction between `hour`/`sun_azimuth:d`



[99]:
```
auto.target_analysis(train_data=X_train, label="y")
```

1.1 Target variable analysis

```
   count         mean         std  min  25%  50%         75%      max   dtypes  \
y  10000   285.096363  774.286536 -0.0  0.0  0.0  160.566251  5596.36  float64

   unique missing_count missing_ratio raw_type special_types
y    2523                                float
```

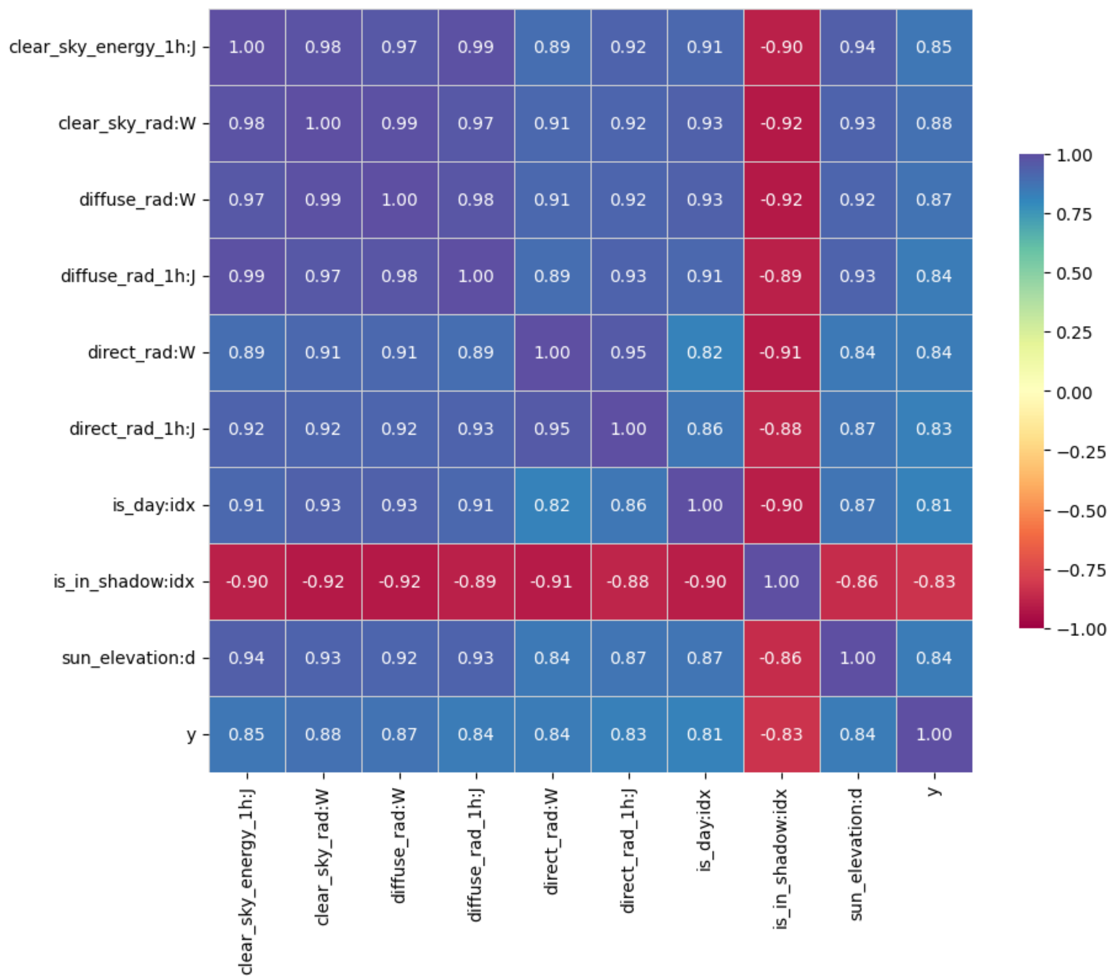


1.1.1 Distribution fits for target variable

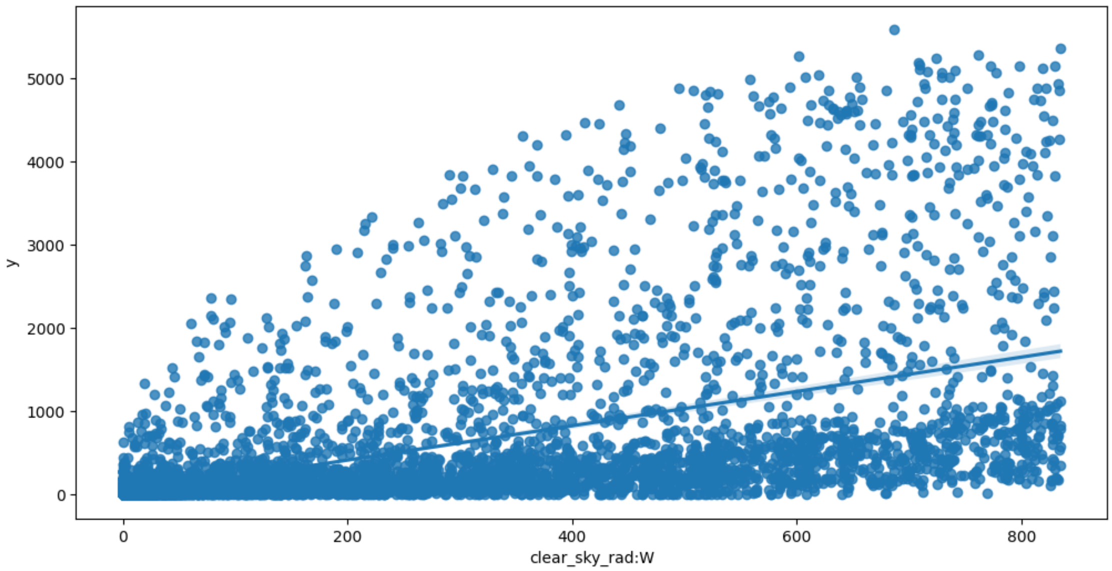
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

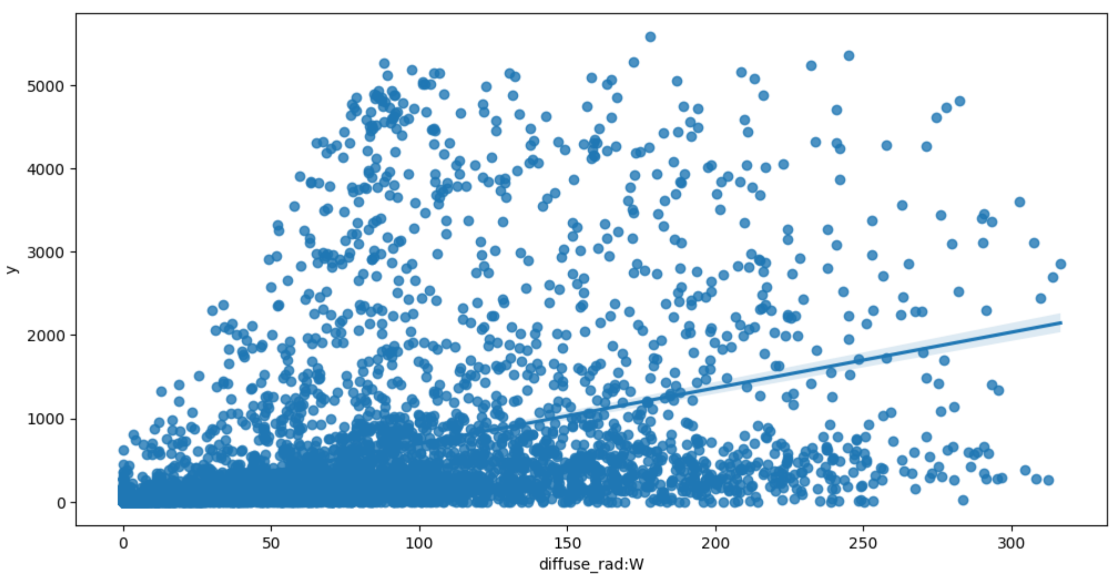
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



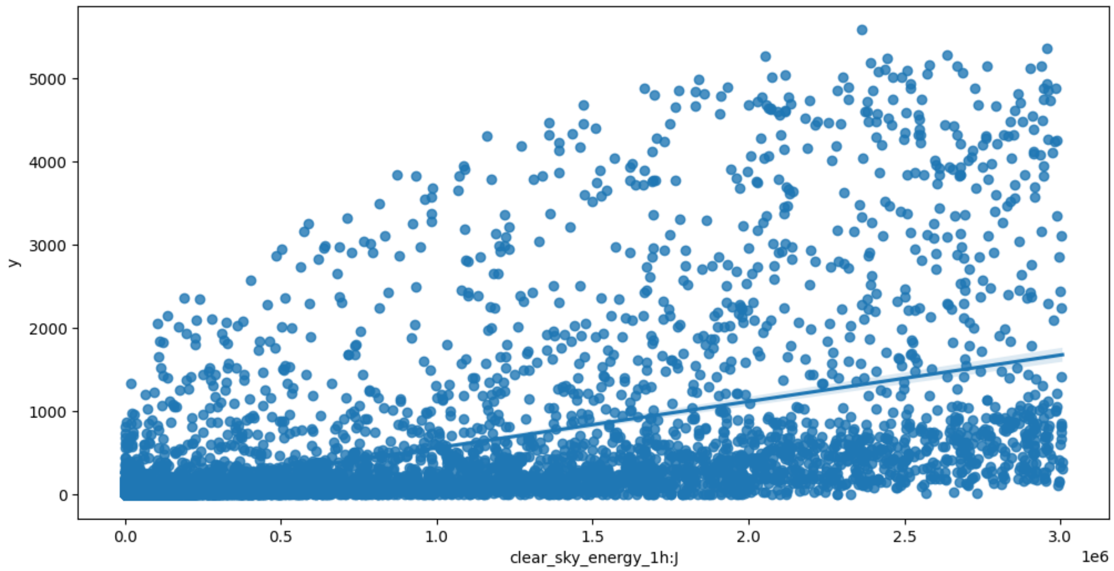
Feature interaction between `clear_sky_rad:W`/`y` in `train_data` (sample size: 10000)



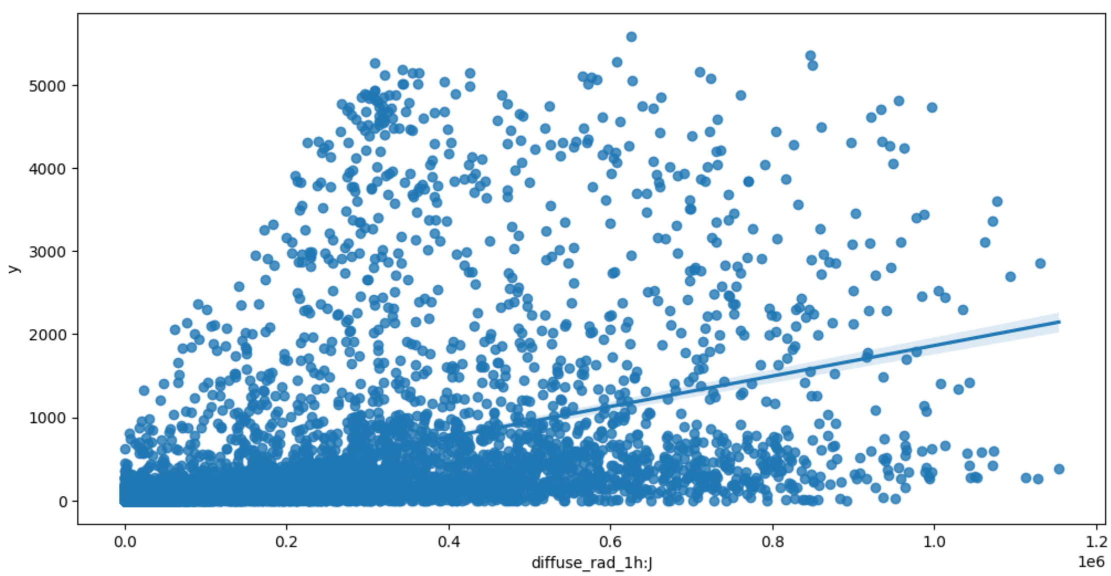
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



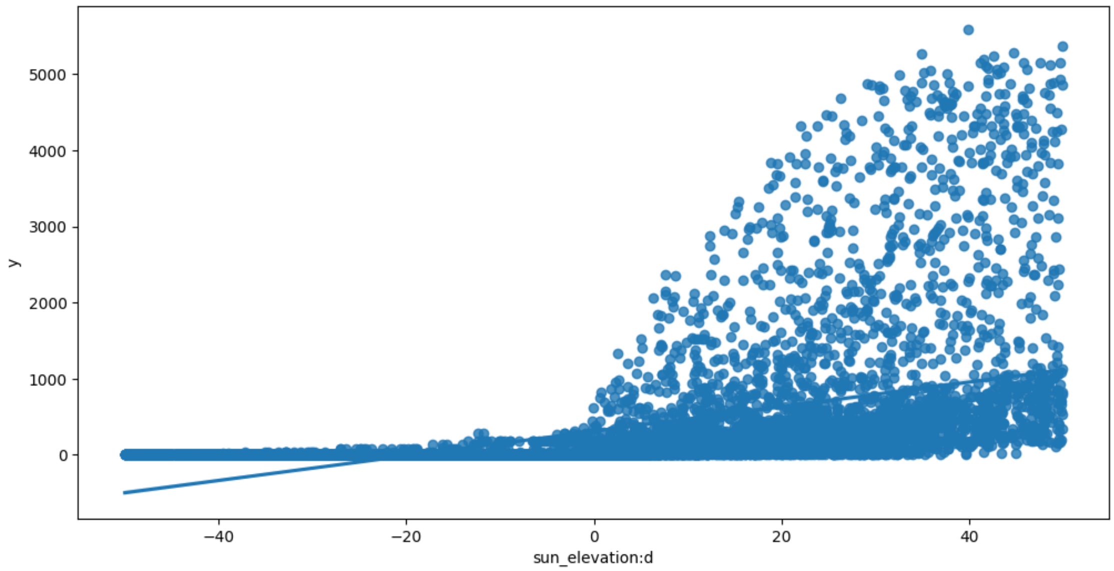
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



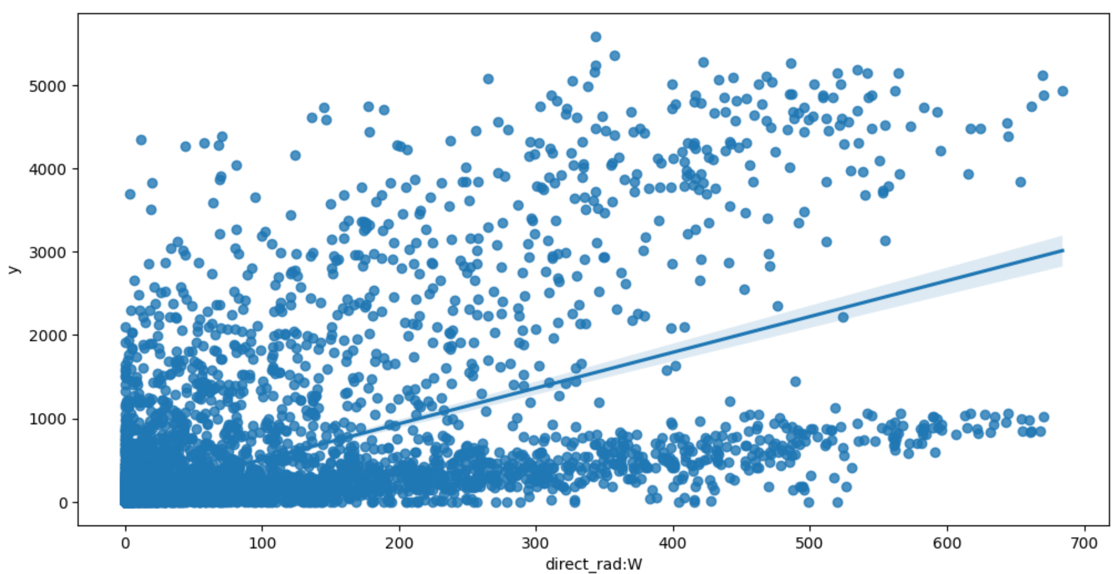
Feature interaction between `diffuse_rad_1h:J/y` in `train_data` (sample size: 10000)



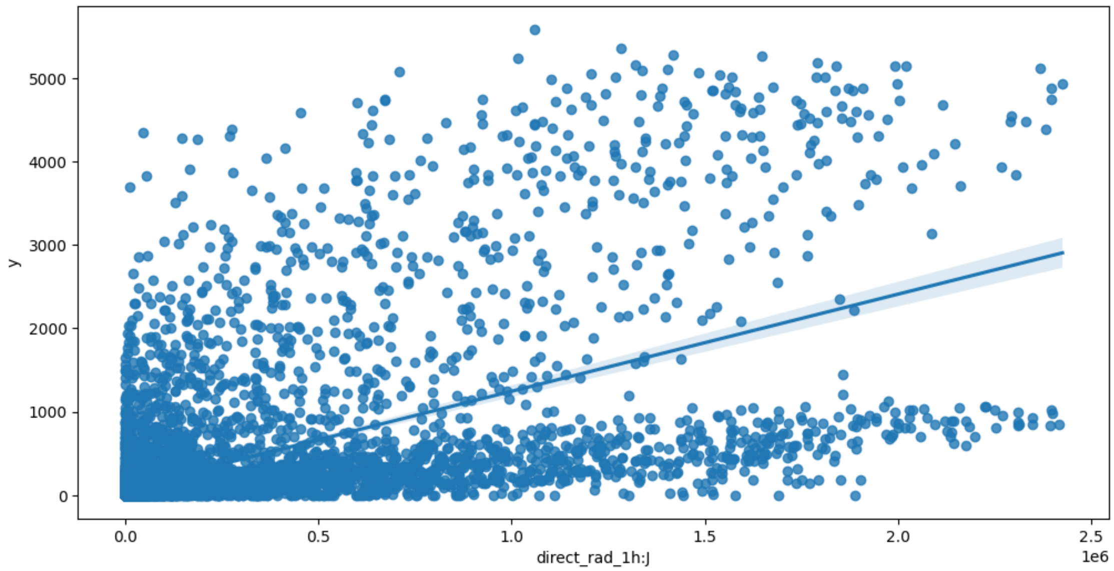
Feature interaction between `sun_elevation:d/y` in `train_data` (sample size: 10000)



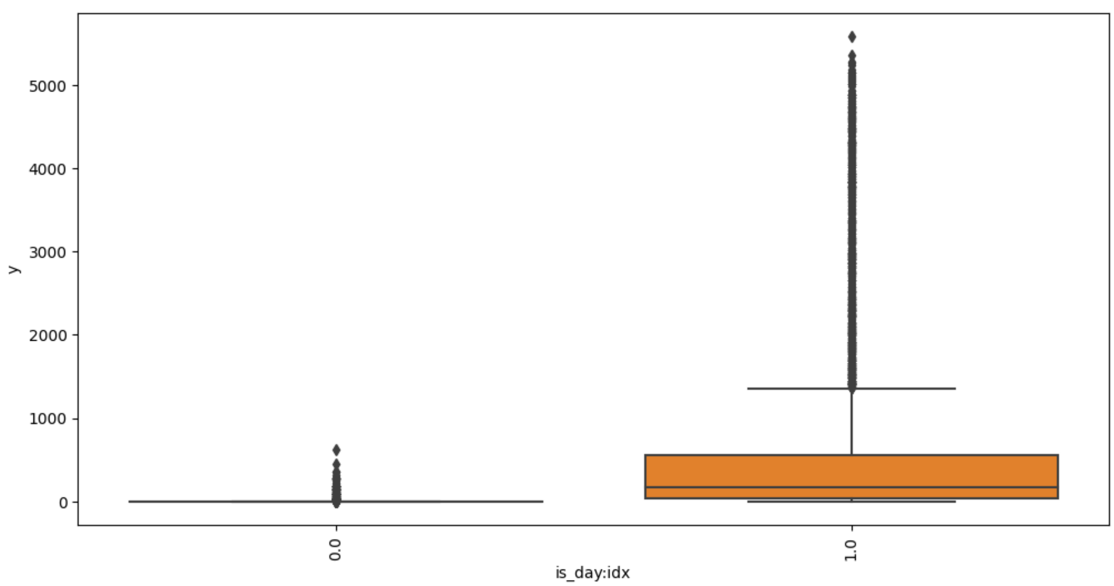
Feature interaction between `direct_rad:W`/y in `train_data` (sample size: 10000)



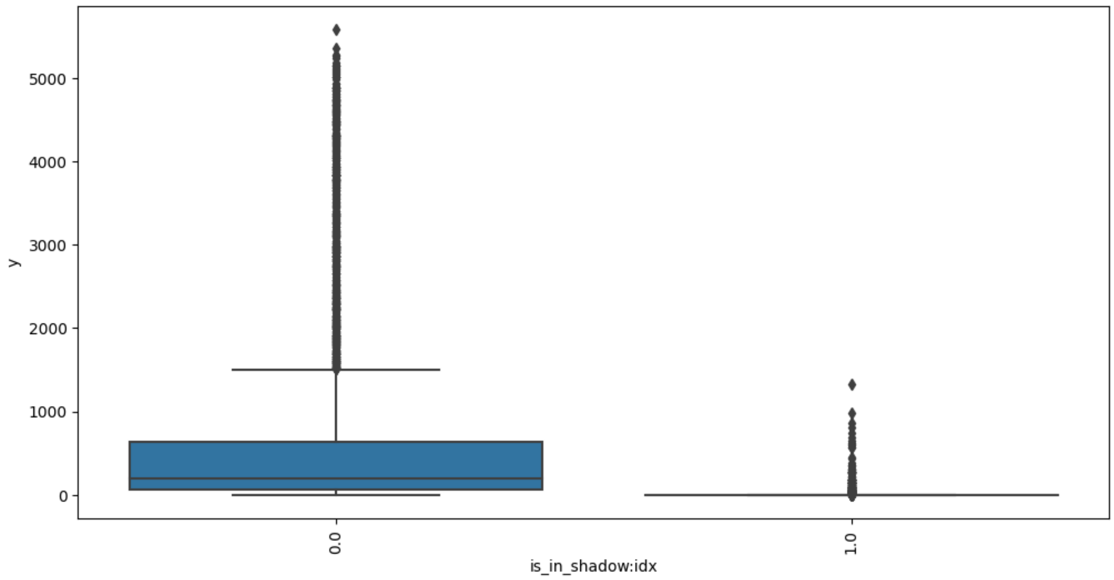
Feature interaction between `direct_rad_1h:J`/y in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx`/y in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx`/y in `train_data` (sample size: 10000)



2 Starting

[100]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 78
Now creating submission number: 79
New filename: submission_79_jorge
```

[101]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)
```

```
label = 'y'
metric = 'mean_absolute_error'
time_limit = 60
presets = 'best_quality'

sample_weight = 'sample_weight' #None
weight_evaluation = True #False
```

```
Loaded data from: X_train_raw.csv | Columns = 53 / 53 | Rows = 92951 -> 92951
```

[102]:
```
predictors = [None, None, None]
```

[103]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
 ↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
 ↪== loc], time_limit=time_limit, presets=presets)
predictors[0] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_jorge_A"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_79_jorge_A/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   15.33 GB / 494.38 GB (3.1%)
Train Data Rows:    34061
Train Data Columns: 51
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 631.01116,
1166.20607)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
```

```
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    5038.42 MB
        Train Data (Original)  Memory Usage: 15.33 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 4 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  6 | ['estimated_diff_hours', 'hour', 'weekday',
'is_weekend', 'month', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  5 | ['estimated_diff_hours', 'hour',
'weekday', 'month', 'year']
                ('int', ['bool']) :  4 | ['is_day:idx', 'is_in_shadow:idx',
'wind_speed_w_1000hPa:ms', 'is_weekend']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.13 MB (0.2% of available memory)
Data preprocessing and feature engineering runtime = 0.11s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
```

```
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.91s of the
59.88s of remaining time.

Training model for location A…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 216.28s compared to 51.86s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 36.69s of the
56.65s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 171.61s compared to 47.67s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 34.12s of the
54.09s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```python
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
↪== loc], time_limit=time_limit, presets=presets)
```

```
predictors[1] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_jorge_B"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_79_jorge_B/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   15.97 GB / 494.38 GB (3.2%)
Train Data Rows:    32819
Train Data Columns: 51
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.89334, 194.00409)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4394.88 MB
        Train Data (Original)  Memory Usage: 14.77 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 4 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
```

```
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  6 | ['estimated_diff_hours', 'hour', 'weekday',
'is_weekend', 'month', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  5 | ['estimated_diff_hours', 'hour',
'weekday', 'month', 'year']
                ('int', ['bool']) :  4 | ['is_day:idx', 'is_in_shadow:idx',
'wind_speed_w_1000hPa:ms', 'is_weekend']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 11.68 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.16s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
```

```
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.88s of the
59.84s of remaining time.
```

Training model for location B…

```
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 160.16s compared to 51.82s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.4s of the
57.35s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 133.14s compared to 48.59s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 35.32s of the
55.28s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -23.1587         = Validation score   (-mean_absolute_error)
        24.39s   = Training   runtime
        65.15s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 0.11s of the 20.06s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -116.8768        = Validation score   (-mean_absolute_error)
        1.21s    = Training   runtime
        0.02s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.84s of the
16.45s of remaining time.
        -23.1587         = Validation score   (-mean_absolute_error)
        0.12s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 16.32s of the
16.3s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -21.9002         = Validation score   (-mean_absolute_error)
        3.87s    = Training   runtime
        1.0s     = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 10.01s of the 10.0s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -21.3768         = Validation score   (-mean_absolute_error)
        1.57s    = Training   runtime
        0.18s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 6.63s of the
6.62s of remaining time.
        -20.3273         = Validation score   (-mean_absolute_error)
        25.22s   = Training   runtime
        0.86s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.84s of the
-19.69s of remaining time.
        -20.3273         = Validation score   (-mean_absolute_error)
        0.2s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 79.91s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_79_jorge_B/")
```

[ ]:
```
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
 ↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
 ↪== loc], time_limit=time_limit, presets=presets)
predictors[2] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_jorge_C"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Values in column 'sample_weight' used as sample weights instead of predictive
features. Evaluation will report weighted metrics, so ensure same column exists
in test data.
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_79_jorge_C/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   15.55 GB / 494.38 GB (3.1%)
Train Data Rows:    26071
Train Data Columns: 51
Label Column: y
Preprocessing data …
```

```
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 77.70004, 165.87752)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4399.47 MB
        Train Data (Original)  Memory Usage: 11.73 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 3 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 42 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  6 | ['estimated_diff_hours', 'hour', 'weekday',
'is_weekend', 'month', …]
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 40 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  5 | ['estimated_diff_hours', 'hour',
'weekday', 'month', 'year']
                ('int', ['bool']) :  3 | ['is_day:idx', 'is_in_shadow:idx',
'is_weekend']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 9.46 MB (0.2% of available memory)
```

```
Data preprocessing and feature engineering runtime = 0.14s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.9s of the
59.86s of remaining time.

Training model for location C…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 105.14s compared to 51.84s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.83s of the
57.79s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 57.03s compared to 49.15s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.69s of the
56.65s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.6035         = Validation score   (-mean_absolute_error)
        19.08s   = Training   runtime
        46.76s   = Validation runtime
```

```
Fitting model: LightGBM_BAG_L1 … Training model for up to 8.83s of the 28.79s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.042  = Validation score   (-mean_absolute_error)
        8.57s    = Training   runtime
        14.81s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.86s of the
16.36s of remaining time.
        -15.5646         = Validation score   (-mean_absolute_error)
        0.1s     = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 16.26s of the
16.25s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -16.1537         = Validation score   (-mean_absolute_error)
        1.9s     = Training   runtime
        0.42s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 12.14s of the 12.13s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.8514         = Validation score   (-mean_absolute_error)
        1.43s    = Training   runtime
        0.13s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 8.85s of the
8.84s of remaining time.
        -15.5697         = Validation score   (-mean_absolute_error)
        17.87s   = Training   runtime
        0.55s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.86s of the
-9.78s of remaining time.
        -15.4504         = Validation score   (-mean_absolute_error)
        0.14s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 69.94s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_79_jorge_C/")
```

3 Submit

[ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 53 / 53 | Rows = 92951 -> 92951
Loaded data from: X_test_raw.csv | Columns = 52 / 52 | Rows = 2160 -> 2160
```

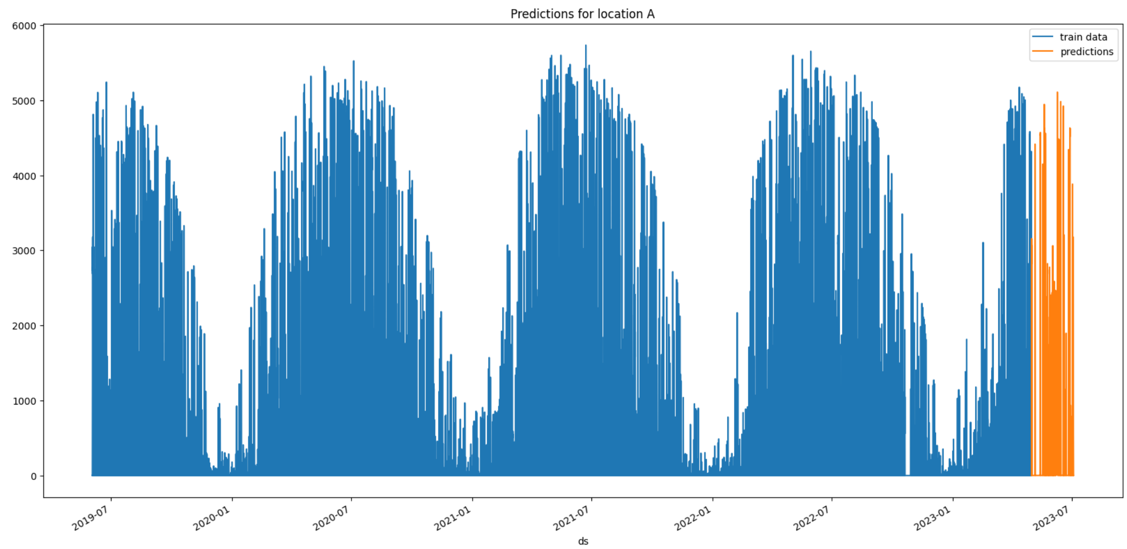
[ ]:
```python
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

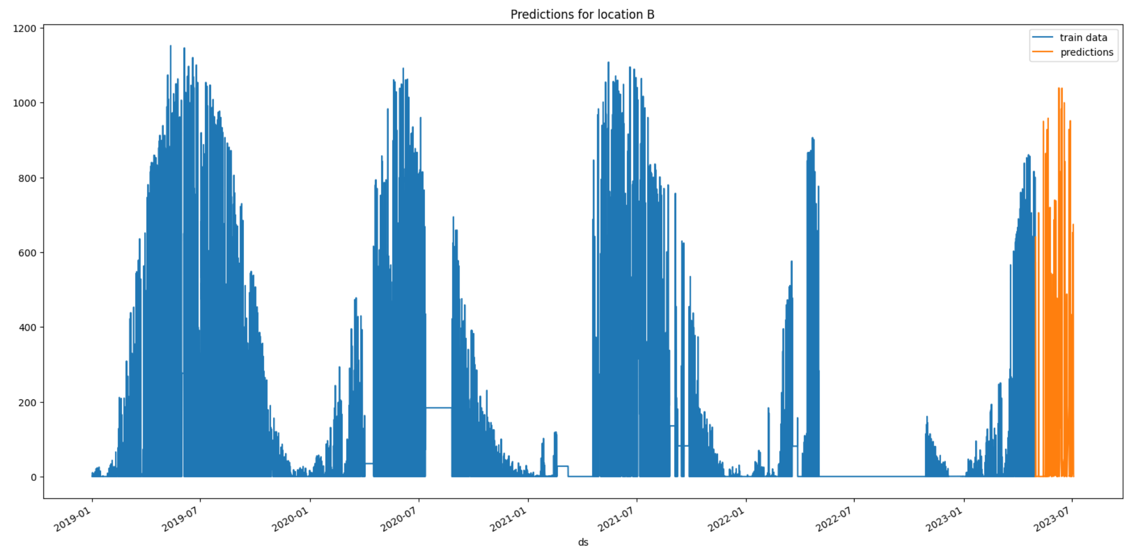
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

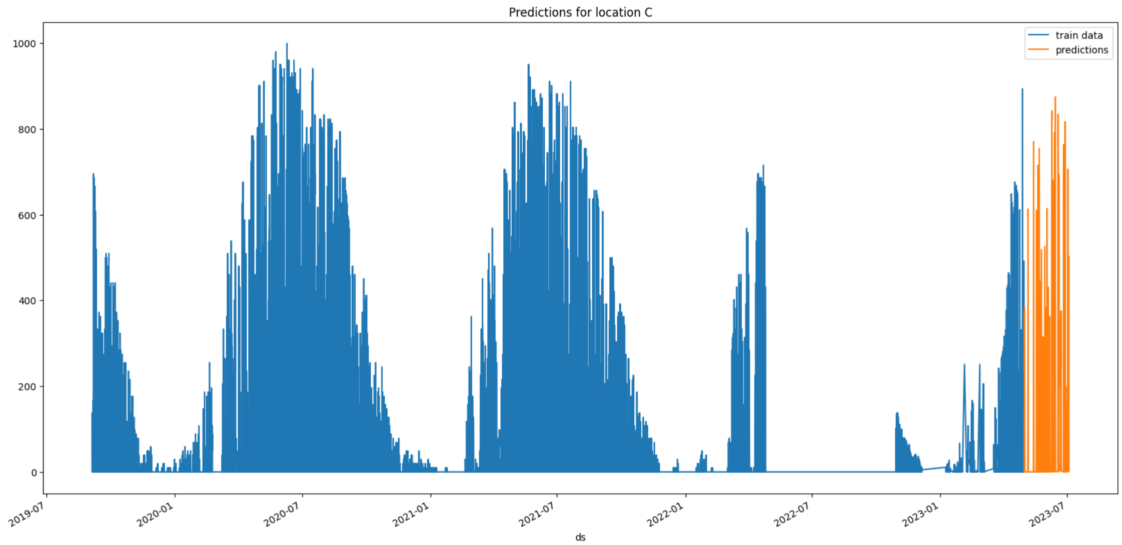
[ ]:
```python
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

[ ]:
```python
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='y', ax=ax, label="train data")
```

```python
# plot predictions
predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

# title
ax.set_title(f"Predictions for location {loc}")
```







[ ]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
       id  prediction
0       0    1.353503
1       1    1.377337
2       2    1.535772
3       3   50.274967
4       4  298.462311
..    …         …
715  2155   91.790527
716  2156   58.327251
717  2157   25.278416
718  2158    3.892292
719  2159    2.036365

[2160 rows x 2 columns]
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
```

```
Saving submission to submissions/submission_79_jorge.csv
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
 ↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_79_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_79_jorge_files/notebook_pdfs
[NbConvertApp] Writing 152138 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1471956 bytes to notebook_pdfs/submission_79_jorge.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_79_jorge.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[ ]:
```
# # feature importance
# location="A"
# split_time = pd.Timestamp("2022-10-28 22:00:00")
# estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
# estimated = estimated[estimated["location"] == location]
# predictors[0].feature_importance(feature_stage="original", data=estimated,␣
 ↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'sample_weight', 'location']
Computing feature importance via permutation shuffling for 48 features using
4394 rows with 10 shuffle sets… Time limit: 600s…
        3094.63s        = Expected runtime (309.46s per shuffle set)
        419.07s = Actual runtime (Completed 2 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[ ]:

	importance	stddev	p_value	n	p99_high \
direct_rad:W	179.527752	0.089041	0.000112	2	183.535682
clear_sky_rad:W	102.034121	0.763313	0.001684	2	136.392434
diffuse_rad:W	76.319510	0.242082	0.000714	2	87.216140
sun_elevation:d	48.306937	1.434587	0.006683	2	112.880735
hour	37.283222	0.841950	0.005082	2	75.181160
sun_azimuth:d	34.812837	0.901175	0.005826	2	75.376611
direct_rad_1h:J	28.456567	0.184929	0.001463	2	36.780617

cloud_base_agl:m	23.171833	0.354225	0.003441	2	39.116231
clear_sky_energy_1h:J	22.080754	0.614640	0.006264	2	49.747021
total_cloud_cover:p	21.249354	0.411635	0.004360	2	39.777903
effective_cloud_cover:p	17.259895	0.014190	0.000185	2	17.898613
month	16.052628	0.649876	0.009110	2	45.304928
ceiling_height_agl:m	15.125792	0.676116	0.010058	2	45.559223
diffuse_rad_1h:J	14.148167	0.011894	0.000189	2	14.683522
relative_humidity_1000hPa:p	13.232798	0.297330	0.005057	2	26.616249
is_day:idx	12.805033	0.807725	0.014188	2	49.162422
wind_speed_u_10m:ms	12.050327	0.464144	0.008667	2	32.942436
weekday	11.374554	0.931762	0.018417	2	53.315108
is_in_shadow:idx	10.136370	0.018201	0.000404	2	10.955648
msl_pressure:hPa	9.303426	0.654040	0.015810	2	38.743145
t_1000hPa:K	8.931381	0.362485	0.009132	2	25.247605
visibility:m	8.547172	0.518337	0.013641	2	31.878598
is_weekend	8.137093	0.320401	0.008860	2	22.559020
wind_speed_10m:ms	7.407126	0.125153	0.003803	2	13.040537
sfc_pressure:hPa	7.345058	0.528305	0.016175	2	31.125179
pressure_100m:hPa	6.942622	0.545800	0.017677	2	31.510253
pressure_50m:hPa	6.667661	0.192459	0.006496	2	15.330645
wind_speed_v_10m:ms	6.375395	0.245266	0.008657	2	17.415344
fresh_snow_24h:cm	5.625596	0.543399	0.021708	2	30.085121
dew_point_2m:K	4.835024	0.656765	0.030480	2	34.397422
estimated_diff_hours	4.296988	0.021430	0.001123	2	5.261618
snow_water:kgm2	4.248560	0.146461	0.007758	2	10.841074
precip_type_5min:idx	2.011457	0.735394	0.080526	2	35.113079
air_density_2m:kgm3	1.468686	0.179319	0.027413	2	9.540235
fresh_snow_12h:cm	1.399083	0.050244	0.008081	2	3.660664
absolute_humidity_2m:gm3	1.260919	0.006155	0.001099	2	1.537983
super_cooled_liquid_water:kgm2	0.855587	0.032606	0.008576	2	2.323244
snow_depth:cm	0.446138	0.040745	0.020528	2	2.280167
precip_5min:mm	0.422909	0.164053	0.085216	2	7.807265
fresh_snow_6h:cm	0.291019	0.010971	0.008483	2	0.784855
dew_or_rime:idx	0.104030	0.001518	0.003285	2	0.172374
prob_rime:p	0.038235	0.014263	0.082092	2	0.680243
snow_melt_10min:mm	0.016844	0.102404	0.427249	2	4.626258
fresh_snow_1h:cm	0.012910	0.006818	0.113768	2	0.319820
fresh_snow_3h:cm	0.002094	0.028007	0.466464	2	1.262740
wind_speed_w_1000hPa:ms	0.000000	0.000000	0.500000	2	0.000000
rain_water:kgm2	-0.032241	0.039702	0.771960	2	1.754814
year	-0.048251	0.020571	0.906799	2	0.877698

	p99_low
direct_rad:W	175.519822
clear_sky_rad:W	67.675808
diffuse_rad:W	65.422880
sun_elevation:d	-16.266861

```
hour                               -0.614717
sun_azimuth:d                      -5.750937
direct_rad_1h:J                    20.132516
cloud_base_agl:m                    7.227436
clear_sky_energy_1h:J              -5.585513
total_cloud_cover:p                 2.720806
effective_cloud_cover:p            16.621176
month                             -13.199671
ceiling_height_agl:m              -15.307639
diffuse_rad_1h:J                   13.612812
relative_humidity_1000hPa:p        -0.150654
is_day:idx                        -23.552357
wind_speed_u_10m:ms                -8.841782
weekday                           -30.566001
is_in_shadow:idx                    9.317091
msl_pressure:hPa                  -20.136293
t_1000hPa:K                        -7.384843
visibility:m                      -14.784253
is_weekend                         -6.284834
wind_speed_10m:ms                   1.773715
sfc_pressure:hPa                  -16.435063
pressure_100m:hPa                 -17.625010
pressure_50m:hPa                   -1.995323
wind_speed_v_10m:ms                -4.664554
fresh_snow_24h:cm                 -18.833928
dew_point_2m:K                    -24.727373
estimated_diff_hours                3.332359
snow_water:kgm2                    -2.343955
precip_type_5min:idx              -31.090164
air_density_2m:kgm3                -6.602862
fresh_snow_12h:cm                  -0.862498
absolute_humidity_2m:gm3            0.983856
super_cooled_liquid_water:kgm2     -0.612070
snow_depth:cm                      -1.387891
precip_5min:mm                     -6.961447
fresh_snow_6h:cm                   -0.202818
dew_or_rime:idx                     0.035686
prob_rime:p                        -0.603772
snow_melt_10min:mm                 -4.592570
fresh_snow_1h:cm                   -0.294000
fresh_snow_3h:cm                   -1.258551
wind_speed_w_1000hPa:ms             0.000000
rain_water:kgm2                    -1.819296
year                               -0.974200
```

[ ]:
```
# # feature importance
# observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
```

```
# observed = observed[observed["location"] == location]
# predictor.feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'sample_weight', 'location']
Computing feature importance via permutation shuffling for 48 features using
5000 rows with 10 shuffle sets… Time limit: 600s…
        4293.33s        = Expected runtime (429.33s per shuffle set)
        359.81s = Actual runtime (Completed 1 of 10 shuffle sets) (Early
stopping due to lack of time…)
```

[ ]:

	importance	stddev	p_value	n	p99_high \
clear_sky_rad:W	34.800616	NaN	NaN	1	NaN
sun_elevation:d	21.053896	NaN	NaN	1	NaN
clear_sky_energy_1h:J	17.959037	NaN	NaN	1	NaN
direct_rad:W	15.484854	NaN	NaN	1	NaN
diffuse_rad:W	8.571135	NaN	NaN	1	NaN
direct_rad_1h:J	3.283643	NaN	NaN	1	NaN
relative_humidity_1000hPa:p	1.839748	NaN	NaN	1	NaN
sun_azimuth:d	1.549566	NaN	NaN	1	NaN
hour	0.997634	NaN	NaN	1	NaN
wind_speed_v_10m:ms	0.907447	NaN	NaN	1	NaN
msl_pressure:hPa	0.676269	NaN	NaN	1	NaN
snow_water:kgm2	0.627690	NaN	NaN	1	NaN
is_day:idx	0.620870	NaN	NaN	1	NaN
precip_type_5min:idx	0.312266	NaN	NaN	1	NaN
wind_speed_10m:ms	0.258658	NaN	NaN	1	NaN
pressure_100m:hPa	0.258171	NaN	NaN	1	NaN
ceiling_height_agl:m	0.255112	NaN	NaN	1	NaN
sfc_pressure:hPa	0.224268	NaN	NaN	1	NaN
pressure_50m:hPa	0.223026	NaN	NaN	1	NaN
precip_5min:mm	0.207318	NaN	NaN	1	NaN
snow_depth:cm	0.079170	NaN	NaN	1	NaN
air_density_2m:kgm3	0.078937	NaN	NaN	1	NaN
fresh_snow_12h:cm	0.077565	NaN	NaN	1	NaN
effective_cloud_cover:p	0.044103	NaN	NaN	1	NaN
snow_melt_10min:mm	0.018210	NaN	NaN	1	NaN
fresh_snow_6h:cm	0.014053	NaN	NaN	1	NaN
fresh_snow_3h:cm	0.004762	NaN	NaN	1	NaN
estimated_diff_hours	0.000000	NaN	NaN	1	NaN
wind_speed_w_1000hPa:ms	-0.000056	NaN	NaN	1	NaN
prob_rime:p	-0.000317	NaN	NaN	1	NaN
fresh_snow_1h:cm	-0.001555	NaN	NaN	1	NaN
dew_or_rime:idx	-0.003530	NaN	NaN	1	NaN
fresh_snow_24h:cm	-0.015575	NaN	NaN	1	NaN
rain_water:kgm2	-0.020746	NaN	NaN	1	NaN

year	-0.021817	NaN	NaN	1	NaN
super_cooled_liquid_water:kgm2	-0.096266	NaN	NaN	1	NaN
cloud_base_agl:m	-0.115793	NaN	NaN	1	NaN
t_1000hPa:K	-0.135829	NaN	NaN	1	NaN
wind_speed_u_10m:ms	-0.223229	NaN	NaN	1	NaN
visibility:m	-0.255399	NaN	NaN	1	NaN
is_weekend	-0.301423	NaN	NaN	1	NaN
weekday	-0.339798	NaN	NaN	1	NaN
total_cloud_cover:p	-0.380572	NaN	NaN	1	NaN
diffuse_rad_1h:J	-0.514786	NaN	NaN	1	NaN
absolute_humidity_2m:gm3	-0.560996	NaN	NaN	1	NaN
month	-0.563007	NaN	NaN	1	NaN
is_in_shadow:idx	-0.585143	NaN	NaN	1	NaN
dew_point_2m:K	-1.026145	NaN	NaN	1	NaN

	p99_low
clear_sky_rad:W	NaN
sun_elevation:d	NaN
clear_sky_energy_1h:J	NaN
direct_rad:W	NaN
diffuse_rad:W	NaN
direct_rad_1h:J	NaN
relative_humidity_1000hPa:p	NaN
sun_azimuth:d	NaN
hour	NaN
wind_speed_v_10m:ms	NaN
msl_pressure:hPa	NaN
snow_water:kgm2	NaN
is_day:idx	NaN
precip_type_5min:idx	NaN
wind_speed_10m:ms	NaN
pressure_100m:hPa	NaN
ceiling_height_agl:m	NaN
sfc_pressure:hPa	NaN
pressure_50m:hPa	NaN
precip_5min:mm	NaN
snow_depth:cm	NaN
air_density_2m:kgm3	NaN
fresh_snow_12h:cm	NaN
effective_cloud_cover:p	NaN
snow_melt_10min:mm	NaN
fresh_snow_6h:cm	NaN
fresh_snow_3h:cm	NaN
estimated_diff_hours	NaN
wind_speed_w_1000hPa:ms	NaN
prob_rime:p	NaN
fresh_snow_1h:cm	NaN

```
dew_or_rime:idx                     NaN
fresh_snow_24h:cm                   NaN
rain_water:kgm2                     NaN
year                                NaN
super_cooled_liquid_water:kgm2      NaN
cloud_base_agl:m                    NaN
t_1000hPa:K                         NaN
wind_speed_u_10m:ms                 NaN
visibility:m                        NaN
is_weekend                          NaN
weekday                             NaN
total_cloud_cover:p                 NaN
diffuse_rad_1h:J                    NaN
absolute_humidity_2m:gm3            NaN
month                               NaN
is_in_shadow:idx                    NaN
dew_point_2m:K                      NaN
```

[ ]:
```
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in
notebook_pdfs/submission_79_jorge_with_feature_importance_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_79_jorge_with_feature_importance_files/notebook_pdfs
[NbConvertApp] Writing 152954 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 1471953 bytes to
notebook_pdfs/submission_79_jorge_with_feature_importance.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_79_jorge_with_feature_importance.pdf',
'autogluon_each_location.ipynb'], returncode=0)
```

[ ]:
```
import subprocess

def execute_git_command(directory, command):
    """Execute a Git command in the specified directory."""
    try:
        result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
```

```
        return result.decode('utf-8').strip(), True
    except subprocess.CalledProcessError as e:
        print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
        return e.output.decode('utf-8').strip(), False

git_repo_path = "."




branch_name = new_filename

# add datetime to branch name
branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

print(branch_name)

commit_msg = "run result"

execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# set git user.name and user.email
execute_git_command(git_repo_path, ['config', 'user.name', 'Jorgen eller␣
↪Henrik'])
execute_git_command(git_repo_path, ['config', 'user.email', 'jorgen.
↪sandhaug@gmail.com'])

# Navigate to your repo and commit changes
execute_git_command(git_repo_path, ['add', '.'])
execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# Push to remote
output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# If the push fails, try setting an upstream branch and push again
if not success and 'upstream' in output:
    print("Attempting to set upstream and push again...")
    execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
    execute_git_command(git_repo_path, ['push', 'origin',branch_name])

execute_git_command(git_repo_path, ['checkout', 'main'])
```

```
[ ]: ('Switched to branch \'main\'\nYour branch is behind \'origin/main\' by 1
     commit, and can be fast-forwarded.\n  (use "git pull" to update your local
     branch)',
      True)
```